Evaluation of i-vector Speaker Recognition Systems for Forensic Application

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Abstract

This paper contributes a study on i-vector based speaker recognition systems and their application to forensics. The sensitivity of i-vector based speaker recognition is analyzed with respect to the effects of speech duration. This approach is motivated by the potentially limited speech available in a recording for a forensic case. In this context, the classification performance and calibration costs of the i-vector system are analyzed along with the role of normalization in the cosine kernel. Evaluated on the NIST SRE-2010 dataset, results highlight that normalization of the cosine kernel provided improved performance across all speech durations compared to the use of an unnormalized kernel. The normalized kernel was also found to play an important role in reducing miscalibration costs and providing well-calibrated likelihood ratios with limited speech duration.

Index Terms: i-vector, speaker recognition, forensics, calibration, short utterances

1. Introduction

One of the potential application areas of automatic speaker recognition is investigation and evidence reporting in forensics. In a typical case scenario, a victim may have received a threatening phone call. The recording of this phone call (referred to as the *trace*) may then be compared to a database of speech samples of known criminals to produce a ranked list of potential suspects. In this scenario the speaker recognition system is used for *investigation* purposes. When a suspect of the crime is found (by the aforementioned search or other means), an automatic speaker recognition system can be used to establish the degree of support that the suspect is the author of the recorded sample—this is referred to as *evidence reporting*. The speaker recognition system in this case must be well-calibrated and should report the strength of evidence as a *likelihood ratio* so as to adhere to modern fact finding conventions in court [1].

The forensic scenario is very challenging for speaker recognition for several reasons. The quality of the trace (e.g., signal-to-noise ratio) can not be controlled and is not known, and the duration of the speech sample can vary from a few seconds to several hours. Further, the recording conditions are often not precisely known making the calibration of the speaker recognition system difficult. These circumstances typically vary from case to case such that finding speech data for system calibration that is representative of the trace conditions becomes a laborious process. An ideal system would be able to produce well-calibrated likelihood ratios without sensitivity to factors such as trace quality and duration, thus allowing each forensic cases to be treated with the same calibrated system.

A speaker recognition system that was reported to exhibit good calibration characteristics during the recent NIST Speaker Recognition Evaluations (SRE) [2] was the state-of-the-art i-vector framework [3]. An i-vector is a compact representation of an utterance extracted from a low-dimensional total variability subspace trained via factor analysis. I-vectors are subject to inter-session compensation before performing speaker detection using a cosine kernel.

In this paper, we investigate the effects of speech duration on the calibration of the i-vector framework for speaker recognition. Focus is given to the the classification performance and calibration costs of the i-vector system that has been developed and calibrated using the homogeneous duration speech dataset. Analysis is expected to highlight where the i-vector framework is sensitive to variations such as speech duration and its mismatch to the dataset used in calibration. Such sensitivities may trivially be dealt with by conditioning the calibration data on exactly the same duration characteristics as the trial at hand [4, 5]. This may be relatively easy for the duration factor studied in this paper, but will be less trivial for factors like signal to noise ratio and room acoustics. As to alleviate the need for this potential laborious process, we hope that by characterizing the duration-dependence of the i-vector system, it will be possible to design methods for dealing with this type of calibration issue.

This paper is structured as follows. Section 2 defines calibration and its role in the context of forensics. Section 3 details the speaker recognition system, speech data sources and experimental setup. The results and analysis are given in Section 4.

2. Calibrating Similarity Scores

For forensic evidence reporting, scores from an automatic speaker recognition system must have the interpretation of a likelihood ratio (LR) in the forensic sense,

$$\text{LR} = \frac{P(E|H_p, I)}{P(E|H_d, I)} \tag{1}$$

where E is the trace (incriminating recording), H_p and H_d represent the prosecutor and defense hypothesis respectively, and I denotes other circumstances relevant to the case. Likelihood ratios can be used in court by the fact finder (judge or jury) to compute the posterior odds,

$$\frac{P(H_p|E, I)}{P(H_d|E, I)} = \text{LR}\frac{P(H_p|I)}{P(H_d|I)} \tag{2}$$

where the second factor is the *prior odds* determined by the court after considering other evidence. Calibration (i.e., converting scores to likelihood ratios) is a difficult task, but the most common way is to use a linear transformation of the

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scores [6]. Calibration then involves optimizing this transformation using a development set of scores to minimize

$$C_{\mathrm{llr}} = \frac{1}{\mathrm{N_{H_p}}} \sum_{i=1}^{\mathrm{N_{H_p}}} \log_2(1 + \frac{1}{\mathrm{LR}_i}) + \frac{1}{\mathrm{N_{H_d}}} \sum_{j=1}^{\mathrm{N_{H_d}}} \log_2(1 + \mathrm{LR}_j) \quad (3)$$

where $\mathrm{N_{H_p}}$ and $\mathrm{N_{H_d}}$ are the number of comparisons in the two hypothesis respectively. The C_{llr} provides an estimation of the calibration error over all priors. Readers are directed to [7] and [8] for further details on calibration and C_{llr}.

3. Experimental method and data

3.1. Speaker recognition system

Features were extracted from audio samples by calculating 19 MFCCs plus log energy from speech audio signals every 10 ms using a 20 ms analysis window. These features were augmented with delta and double-delta coefficients. Speech activity detection (SAD) was implemented in the same manner as described in [9]. Finally, feature warping [10] was applied to all features using a 5-second analysis window. Gender-dependent, 2048-component UBMs were trained using data sourced from Switchboard II: Phase 3, Switchboard Cellular (Parts 1 & 2), Fisher English and NIST SRE 2004–2006 corpora.

The i-vector system for which we will study the calibration behavior w.r.t. duration follows the framework described by Dehak *et al.* [3]. A single dataset compiled from the aforementioned datasets and additional interview data sourced from the NIST 2008 SRE follow-up corpus was used for development of the i-vector system including total variability subspace, LDA transform and WCCN matrix training. A total variability subspace of 400 dimensions was used to extract i-vectors for all relevant speech segments. LDA was used to reduce these i-vectors to 200 dimensions after which WCCN was employed to further reduce the effects of channel variability thereby following the typical i-vector recipe as detailed in [3].

Comparison of two i-vectors (referred to as the train and test i-vectors) was conducted using a cosine kernel. Throughout this study, the beneficial effect of cosine kernel normalization [11] is investigated in the context of performance and calibration. Cosine kernel normalization can be viewed as a re-centering of the i-vector space based on a set of held-out i-vectors. Normalization was implemented using the same dataset used for i-vector system development mentioned above.

3.2. Evaluation and calibration data

We use NIST SRE-2010 evaluation data [2] to characterize the performance of our i-vector system. Although our system has been developed to deal with a variety of recording, speaking style and vocal effort conditions [9], in this work we concentrate on the telephone trials (a.k.a. 'condition 5') as this condition appears most relevant to the forensic cases. We use the 'extended core test' trial list distributed by NIST after the official submission deadline, which consists of 416119 trials, as this leads to better error measurement statistics than the original trial list that has far fewer trials.

The core condition consists of 5-minute conversations, where each conversation side was typically found to contain 80 seconds of active speech. In order to study the effect of duration, we synthesized test and train data sets of 5, 10, 20, 40 seconds by truncating the feature streams after SAD[1]. For consistency in our results, the conversation sides that contained less that 40 seconds of nominal speech using our speech detection algorithm were discarded from all results reported in this work.

Ideally, we would have used NIST SRE-2008 data for the purpose of score calibration performed in Section 4.3. However, as this was used in the development of the i-vector system, we reverted to splitting the SRE-2010 extended trial list in two halves, each with a disjoint set of 204 target speakers. One half was then used for training the calibration parameters, and the other for the purpose of evaluation.

3.3. Experimental setup

Experiments were carried out using evaluation data with a speech duration of $d = 5\,\mathrm{s}, 10\,\mathrm{s}, 20\,\mathrm{s}, 40\,\mathrm{s}$ as well as full length utterances. An exhaustive set of duration combinations were trialled so as to adequately analyze the effect of duration mismatch in the i-vector system. Here, we also varied whether or not cosine kernel normalization was applied. Along with performance properties, the characteristics of the target and non-target score distributions were analyzed.

The last set of experiments concern system calibration. Linear calibration was performed using the FoCal toolkit [6], where scores for training the calibration parameters were sourced from the calibration portion of the full-full train-test duration combination (as defined in Section 3.2). The calibration parameters (an offset and a linear scaling) were learned using logistic regression, and applied to the evaluation half of the trials of all the different duration conditions. Thus, there was no overlap between target speakers in calibration training and evaluation, but there was a mismatch between the duration of the segments used for calibration and evaluation.

3.4. Performance characterization

Discrimination performance of our system is reported in terms of EER and $C_{\mathrm{det}}^{\mathrm{min}}$, with $C_{\mathrm{miss}} = 10, C_{\mathrm{FA}} = 1, P_{\mathrm{tar}} = 0.01$. These are the 'traditional' NIST cost parameters used for the short duration conditions in SRE-2010 involving 10-second segments and all SREs prior to 2010. In order to study how well our system was calibrated, we used C_{llr} [7, 8] and $C_{\mathrm{llr}} - C_{\mathrm{llr}}^{\mathrm{min}}$, the latter showing the costs of the log-likelihood due to miscalibration. A system is deemed well-calibrated when it has a low miscalibration cost and is, therefore, able to provide more reliable likelihood ratio values.

4. Results

In this section, we present and analyze the performance of our i-vector system with respect to varying speech duration in terms of classification performance, corresponding effects on score distributions and miscalibration cost. The use of both cosine kernel and normalized cosine kernel scoring is investigated.

4.1. Basic performance results

As an initial starting point, we investigate the effect of varying utterance duration on the performance of the i-vector based

[1]Note that we did not use the data form the '10 second' training and test conditions from NIST, because these have not been distributed in the 'extended' version, and moreover, we wanted to study duration dependence in a wider range of durations.

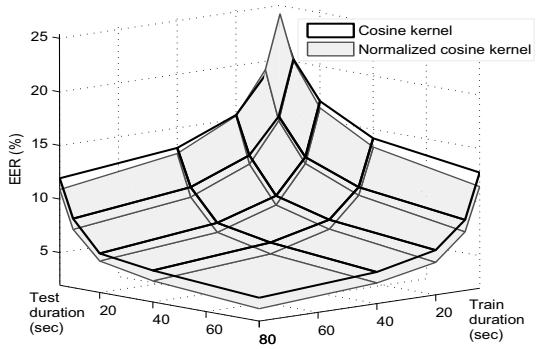


Figure 1: The EER from the i-vector system using different cosine kernels with respect to train and test speech duration.

speaker recognition system. The corresponding EER values for both cosine kernel conditions are presented in Figure 1. It can be observed that the error rate increased as the train and test duration was reduced, which characterizes the typical behavior of most classifiers in speaker recognition [4, 5]. Noteworthy is the symmetry of the EERs around the point of matched train and test duration in Figure 1—that is, the i-vector system provided comparable EER when the train and test durations are swapped. This characteristic is distinct from other classifiers that typically treat the train speech segments different to the test speech segments. The symmetry of the i-vector system, therefore, contributes a simplistic configuration in that a distinction between train or test utterance does not have to be made when dealing with speech samples of mismatched duration.

Observing EER trends in Figure 1, we see that the i-vector system with a normalized kernel has, in general, better performance across all duration combinations than the unnormalized kernel. This is of interest as the cosine kernel normalization was based solely on a full-length utterance dataset. Other classifiers such as support vector machines and joint factor analysis (JFA) require that the dataset used for score normalization be matched to the evaluation condition in order to maintain reasonable classification performance [4, 5]. Although not shown here, similar trends between the unnormalized and normalized system were also found in terms of $C_{\text{det}}^{\text{min}}$.

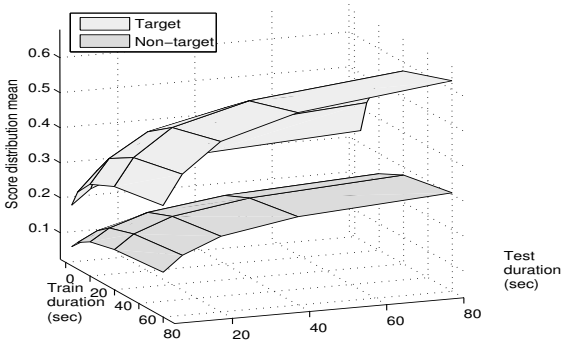
To better analyze the system performance at specific train and test durations, $C_{\text{det}}^{\text{min}}$ and EER values from several duration combinations are presented in Table 1. From the matched train-test duration combination trials, it can be observed that the system performance was reduced by close to a factor of two as the duration of speech was halved. Full-length utterance training, on the other hand, provided a more graceful reduction in the system performances. These trends along with the symmetrical behavior of the i-vector system are of particular interest in forensic evidence reporting where long speech samples can be collected from a suspected speaker in an interview scenario, while the trace may be of uncontrolled duration.

4.2. Score distributions

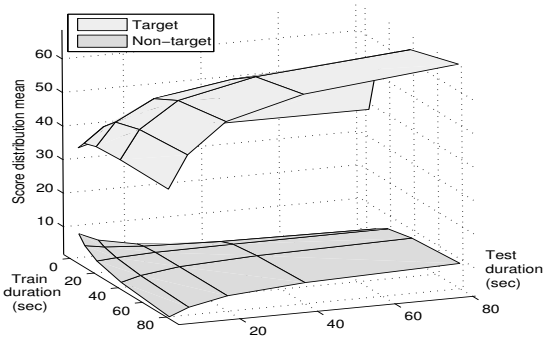
We performed experiments to analyze the system score distributions by looking at the mean and standard deviation of the target and non-target scores with respect to varying train and test durations. Figure 2 shows the mean of both scores distributions from these experiments when using the unnormalized and normalized cosine kernels. It can be seen from Figure 2(a) that there was a negative shift in both score distributions of the unnormalized system as the speech length was reduced. In contrast, Figure 2(b) indicates that the normalized system provided a relatively stable non-target score mean along with a more uniform separation between the target and non-target scores.

Duration (sec)			
Train	**Test**	$\mathbf{C_{det}^{min}}$	**EER (%)**
full	full	0.016	3.11
full	40	0.019	3.92
full	20	0.024	4.89
full	10	0.035	7.39
full	5	0.049	10.88
40	40	0.024	4.81
20	20	0.038	7.67
10	10	0.063	14.68
5	5	0.088	24.23

Table 1: Minimum DCF and EER value of several duration combination trials in normalized i-vector system.



(a) Cosine Kernel



(b) Normalized Cosine Kernel

Figure 2: The mean of the target and non-target score distributions from i-vector systems using different cosine kernels

Table 2 details the mean and standard deviation of the standard deviations of the target and non-target score distributions when using both kernels in the i-vector system. Limited fluctuation occurred in the standard deviation of the score distributions as indicated by the low σ relative to the average standard deviation μ. Thus, the standard deviation of the i-vector scores have a limited sensitivity to the length of speech duration and the application of the cosine kernel normalization.

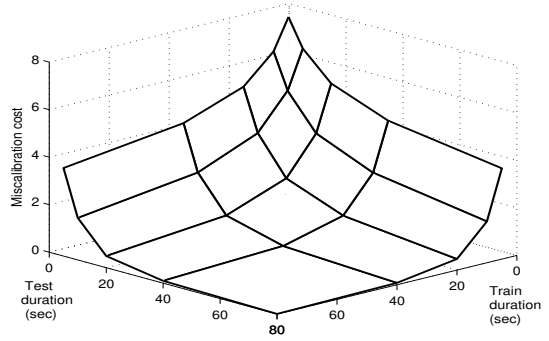
4.3. Calibration experiments

A well-calibrated system is required when using an automatic speaker recognition system in forensic application for presenting evidence to court. Here we analyze the calibration in terms of the extra costs C_{llr} due to miscalibration.

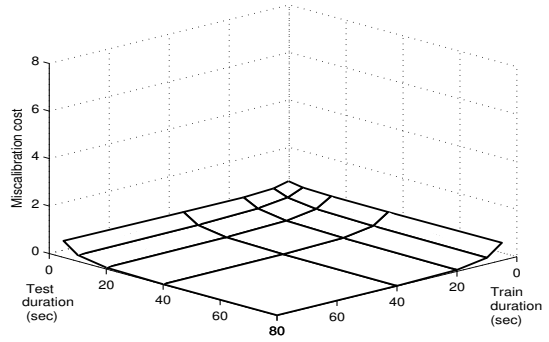
The values of C_{llr} representing several duration conditions

Score Distribution	Cosine μ	Cosine σ	Norm. Cosine μ	Norm. Cosine σ
Target	0.084	0.002	17.5	1.16
Non-target	0.082	0.004	14.8	0.63

Table 2: Statistics of the standard deviation of the target and non-target score distributions across all duration combinations.



(a) Cosine Kernel



(b) Normalized Cosine Kernel

Figure 3: Miscalibration cost for female trials using different cosine kernels with respect to train and test speech duration

for the female speakers are shown in Table 3, where the breakdown in discrimination ($C_{\text{llr}}^{\text{min}}$) and miscalibration ($C_{\text{llr}} - C_{\text{llr}}^{\text{min}}$) can be appreciated. The miscalibration cost rapidly increased in the unnormalized system as speech duration was reduced, driving the costs up to far beyond $C_{\text{llr}} = 1$. Note that a non-informative system producing LR $= 1$ for any input trial has $C_{\text{llr}} = 1$, so for short durations this calibration would be considered *very poor*. The miscalibration costs for both cosine kernels are depicted graphically in Figure 3. By comparing Figure 3(a) and Figure 3(b), it can be observed that the miscalibration cost is reduced dramatically w.r.t. normalization in the cosine kernel scoring. Nonetheless, even in the case of the normalized kernel, the full-utterance calibration produced damaging log likelihood-ratios for the shorted durations (cf. Table 3).

5. Conclusions

In this paper we analyzed the effect of a quality factor from the speech signal (in this case utterance duration) to the performance of a modern speaker recognition system in terms of discrimination and calibration. We used fixed calibration parameters trained on scores from full-length utterance trials. This showed that duration variation has quite an influence on the quality of the LR, in some cases producing C_{llr} costs larger than one which indicates that such a system should *not* been used in those duration conditions. Normalization of the cosine kernel was found to be helpful, particularly in the reduction of calibration costs for this i-vector system.

Duration Train	Duration Test	Cosine C_{llr}	Cosine $C_{\text{llr}}^{\text{min}}$	Norm. Cosine C_{llr}	Norm. Cosine $C_{\text{llr}}^{\text{min}}$
full	full	0.15	0.14	0.13	0.12
full	40	0.28	0.18	0.17	0.16
full	20	0.71	0.22	0.26	0.19
full	10	2.09	0.31	0.54	0.28
full	5	4.10	0.39	1.07	0.37
40	40	0.54	0.21	0.22	0.19
20	20	2.22	0.32	0.48	0.30
10	10	5.48	0.51	1.02	0.50
5	5	8.45	0.70	1.62	0.73

Table 3: C_{llr} and $C_{\text{llr}}^{\text{min}}$ values for female scores with respect to train and test speech duration for the i-vector system using both unnormalized and normalized cosine kernels.

There are ways to deal with this calibration phenomenon. One is to re-calibrate for every possible duration condition using development data of matching duration, which can be laborious and does not generalize trivially to other quality factors or very long duration conditions. A better way would be to include the quality factor in the calibration model as 'side information,' which still needs calibration data of similar conditions, but hopefully the calibration model can interpolate for unseen duration conditions. Our future work includes the investigations on such calibration models, and extending the analysis to other quality factors such as signal to noise ratio and room acoustics.

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